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Development of fuzzy models for asphalt pavement performance

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ABSTRACT. The objective of this paper was to develop fuzzy models for asphalt pavement performance. The fuzzy logic can convert linguistic or qualitative variables into quantitative values. This feature makes it possible to gather experts' experience about the knowledge they have on factors that affect the pavement performance and its state condition. Forms developed in an organized way were applied for acquiring the knowledge from experts on pavement construction and maintenance. The variables pavement age, traffic, International Roughness Index (IRI) and Flexible Pavement Condition Index (FPCI) were associated with numerical scales and linguistic concepts such as new, old, light, heavy, good, fair, and poor. From the information obtained through the application of forms, variables were modeled with the aid of software InFuzzy and fuzzy models were developed for IRI and FPCI. For validating the model, a straight line adjustment was used to relate the predicted to the observed data. Also, the corresponding correlation coefficient (r) was calculated and residuals were analyzed. The developed models fitted to observed data and correlation coefficient r = 0.71 and 0.70, respectively.

Keywords: pavements; management systems; performance models.

Introduction

A Pavement Management System (PMS) is a set of methods that assists decision makers in finding better strategies to provide and maintain pavements in proper serviceability conditions for a certain period of time. Its function is to increase the possibilities of decisions and to improve their efficiency. A PMS is also used to assess the consequences of decisions, to facilitate the coordination of activities within a road agency, and to ensure the consistency of decisions taken at different levels of management within the same organization.

Predicting models for pavement condition are part of a PMS and they are used both at network level, for planning, estimating the total requirements of maintenance and rehabilitation, project prioritization, and scheduling investments; and at project level, for defining maintenance and rehabilitation activities. Failures in the prediction process for the future pavement condition may result in choosing mistaken strategies and, hence in inefficient use of resources. The pavement performance models can be classified as mechanistic, empirical-mechanistic, empirical, and subjective.

The mechanistic models exclude the empirical inferences on estimating the pavement deterioration. All the responses and their effects on pavement structure are purely mechanistic and based on physical representation of the deterioration process, which is represented by response parameters such as stresses, strains and deflections. The empirical-mechanistic models usually correlate structural responses (stresses, strains and displacements) with experimental data on the evolution of structural or functional deterioration of pavements.

Empirical models relate a particular pavement performance index to independent variables, such as traffic load, usually represented by the Equivalent Single Axle Load (ESAL), or the environmental effects, usually represented by the number of years, which quantify the climate cycles. The subjective models are developed based on the experience and knowledge acquired by experts responsible for managing a particular network. These models are developed using techniques that assist the designer on gathering the experience in an organized way.

The objective of this paper was to develop fuzzy models for asphalt pavement performance. The fuzzy logic has as its main feature the conversion of linguistic, vague, imprecise, and qualitative expressions into

numerical values, in order to convert human experience into an understandable way to the computer language. For developing the fuzzy modeling, it was necessary to obtain expert's judgments on variables that affect the pavement performance and pavement condition indices, such as International Roughness Index (IRI) and Flexible Pavement Condition Index (FPCI), as well as the required fuzzy rules for developing the models. This information was obtained through forms applied to experts.

The fuzzy logic can convert vague and qualitative information into quantitative data. According to Simões and Shaw (2007), the fuzzy logic represents a way of handling inaccurate information, translating verbal expressions, common in human communication, into numerical values. Thus, it has a large practical importance, as it enables to include expert's experience, enabling better decision-making strategies in more complex problems, such performance pavement.

Kaur and Tekkedil (2000) developed an expert system based on fuzzy logic to predict the rut depth of asphalt pavements, given the parameters of construction materials, pavement thickness, road age and traffic count. In their research, the long-term pavement performance (LTPP) database was used. The data extracted from this database was used for designing and testing the fuzzy inference system. The membership functions of all the input parameters were built in accordance with these database records. The rules that defined the behavior of the fuzzy inference system were written considering the data available as well as using logical reasoning. The resulting system was able to predict possible rut depths on pavement up to 15 years since its construction. A correlation of 0.700829 was obtained between the measured readings available in the data and the output obtained by the fuzzy inference system. The regression analysis performed on the data gave an R-squared factor of 0.92 for the fuzzy model and 0.78 for the actual data. This indicates that the fuzzy expert system resulted in a much better estimate for the prediction of the pavement performance than the original data.

Chen and Flintsch (2007) proposed a fuzzy logic approach to determine the appropriate maintenance, rehabilitation time, in a probabilistic model to analyze the pavement life cycle cost. Instead of determining a pre-scheduled service time during construction and future rehabilitations, the proposed approach uses the fuzzy logic and performance curves creating models to determine the most appropriate time for maintenance, rehabilitation and reconstruction activities.

Chandran, Isaac, and Veeraragavan (2007) used the mathematics of fuzzy sets to infer about the subjectivity of human judgements on the severity and extent of pavement distresses. Membership functions were formulated for severity, extent, and the importance of each distress as well as the respective appropriate maintenance activity.

Pan, Ko, Yang, and Hsu (2011) developed a method to assess the pavement condition index by using five membership functions and estimated the pavement condition by using fuzzy regression to better account the uncertainties of the traditional method (conventional regression). Also, a similarity indicator was applied to measure the goodness of fit. A case study using pavement inspection data was presented to establish estimated fuzzy regression equations. The results demonstrate the capability of the model, which is able to assist road administration units to determine desirable repair actions regarding the predicted pavement conditions.

Ouma (2015) evaluated a multi-attribute approach that compares fuzzy Analytical Hierarchy Process (AHP) and fuzzy Technique for Order Preference by Ideal Situation (Topsis). The pavement distress data was collected through empirical condition surveys and rated by pavement experts. In comparison to the crisp AHP, the fuzzy AHP and fuzzy Topsis pairwise comparison techniques were considered to be more suitable for subjective analysis of pavement conditions for automated maintenance prioritization. From the case study results, four pavement maintenance objectives were determined as road safety, pavement surface preservation, road operational status and standards, and road aesthetics, with corresponding depreciating significance weights of $W = [0.37, 0.31, 0.22, 0.10] T$. The top three maintenance functions were identified as Thin Hot Mix Asphalt (HMA) overlays, resurfacing and slurry seals, which were a result of pavement cracking, potholes, raveling, and patching, while the bottom three were cape seal, micro surfacing, and fog seal. The two methods gave nearly the same prioritization ranking. In general, the fuzzy AHP approach tended to overestimate the maintenance prioritization ranking as compared to the fuzzy Topsis.

Fuzzy logic

The characteristic function of a set can be generalized in order to associate, within a range, a value for each element from this set, which reflects the degree of truth to the set. The compatibility of each element to a fuzzy set is called degree of truth. The membership functions' codomain is the interval [0,1].

According to Zadeh (1965 apud Silva et al., 2013), the fuzzy logic consists of three stages: fuzzification, rule evaluation, and defuzzification. The fuzzification converts the variables of the problem into linguistic variables (natural language). As revealed by Ganga, Carpinetti, and Politano (2011, p. 759), this step is a mapping between numerical values from input variables into degrees of truth with linguistic concepts. "The role of an expert in the subject to be modeled has major importance to assist in formulating the membership functions to describe the input data".

The rule evaluation is the most important stage of fuzzy logic, since it is in this stage that the decisions made are carried out. Moreover, the logic that allows conclusions from known facts and input and output linguistic variables is performed at this point. This step is related to the fuzzy rules (Zadeh, 1965 apud Silva et al., 2013). The objectives and control strategies used by experts are described by the fuzzy rules through a set of decisions, usually linguistics. From a set of input conditions (antecedent), the control actions for the consequent are generated (Simões & Shaw, 2007).

Lastly, the defuzzification stage which consists of obtaining discrete values for the output variables is performed. This step transforms linguistic concepts obtained by the rule evaluation stage into numerical values, which are used as fuzzy system outputs. The most widespread methods for defuzzification are: center of area; center of maxima, and the mean of maximum method (Ganga et al., 2011).

Material and methods

The antecedent (set of independent variables) used in this study consisted of the age of the pavement since its construction (ID) and the equivalent single axle load (Esal) number of 80 kN (N). The consequent (set of dependent variables) was composed of the International Roughness Index (IRI) and the Flexible Pavement Condition Index (FPCI).

It was established that the degree of truth for each variable varies on a scale from 0 to 1. When a value definitely does not belong to a certain group, the degree of truth associated with this condition is zero. As the degree of truth increases, the degree of belonging to a condition increases as well. In this research, the range of degrees of truth was 0, 0.25, 0.50, 0.75, reaching a maximum value of 1, which shows that this value belongs completely to this group.

Data collection

Forms were developed to be applied to pavement management experts so that their judgments were used to build the models. The forms were created using Excel spreadsheets indicating both numerical scales of variables and sets of linguistic variables.

The variable age of the pavement (ID) was divided into two-year intervals on a scale from 0 to 20 years. Three groups were defined for this variable: New Pavement (PN); Middle age pavement (PM); and Old Pavement (PA). Each expert could choose an option on the form for each value of age according to the degree of truth associated with each group. The Equivalent Single Axle Load of 80 kN (N) represents the traffic in a highway section since its construction and its value ranged from 0 to 100,000,000. Within this interval, there were three groups: Light Traffic (NL); Medium Traffic (NM); and Heavy Traffic (NP).

The scale used for IRI ranged from 1.0 to 6.0 m km^{-1}, with 0.5 m km^{-1} intervals. The groups defined for this variable were very good IRI (IRIO), regular IRI (IRIR), and poor IRI (IRIP). For FPCI, the scale used ranged from 0.0 to 5.0, with 0.5 intervals. For choosing the degree of truth, the groups created were very good FPCI (ICPFO), regular FPCI (ICPFR), and poor FPCI (ICPFP).

For this research, a rule-based fuzzy system was utilized as the fuzzy controller. The fuzzy rules were obtained through the forms applied to the experts to generate the inference rules for each output variable. In this way, when each group of pavement age (PN, PM and PA) was associated with each group of the Esal number (NL, NM and NP), a fuzzy rule was obtained. In total, there were nine fuzzy rules (combination between groups of variables ID and N).

The fuzzy rules used to obtain the indices followed the pattern 'if' cause 'then' effect. This inference logic, also called defuzzification of the process, defines the subjective modeling that was applied in a fuzzy modeling computational tool to assist in the development of models. Bellow, an example of fuzzy rule is presented.

'*IF* New Pavement (PN) *AND* Light Traffic (NL) *THEN* IRI = IRIO and FPCI = ICPFO'

Experts in pavement management were consulted through forms. In total, seven experts were surveyed: four regional coordinators of Deer/MG (*Departamento de Edificações e Estradas de Rodagem de Minas Gerais*),

a maintenance manager of a road concessionaire in the State of São Paulo, and two professors of Federal Higher Education Institutions. Each interviewed expert responded to five forms (two input variables, two output variables and one form for fuzzy rules) judging, according to his experience, the pavement condition for the intervals and established groups. Figure 1 illustrates an example of the form for age of pavement responded by one of the experts.

For treatment and analysis of forms, the averages and standard deviations of degrees of truth were obtained. The degrees of truth outside the standard deviation interval were not considered in this research. For the fuzzy rules, the trend of answers was utilized, prevailing answers that occurred more often in total.

Software InFuzzy

The modeling and simulation process of fuzzy systems in this study was performed by a computational tool called 'InFuzzy'. The software received the membership functions obtained from the average of answers in the forms for each input and output variable. It was also defined, in this software, the fuzzy rules that the model would follow for defuzzification process. Figure 2 shows the modeling of the variable IRI in the InFuzzy, obtained according to experts' judgments.

The degrees of truth are presented on the vertical axis and the considered IRI interval ranging from 0 to 6 m km^{-1} is presented on the horizontal axis. The curves in Figure 2 represents, respectively, from left to right, the degrees of truth for numerical values within the interval for the groups Irio, Irir, and Irip, modeled from the experts' answers.

For the defuzzification process and the obtaining of discrete values for IRI and FPCI, the center of area method was used. This method was chosen since it is recommended for modeling overlapping functions, as in this study. Likewise, this method showed better results compared to other methods, after running simulation with the models. Figure 3 presents a result of defuzzification process for simulating the IRI, with input values of ID equal to 14 years and N equal to 1,470,000.

Once the input and output functions and the fuzzy rules were defined, the simulations were performed with input data of age of pavement and traffic used by Soncim, Fernandes, and Campos (2013), provided by Derba (*Departamento de Infraestrutura de Transportes da Bahia*) with data of sections from highways of the State of Bahia. Sections were randomly selected from this database for analysis.

Results and discussion

Calculated values from developed fuzzy models were compared to observed values for IRI and FPCI indices. Table 1 and 2 list the observed values, calculated values, and residues for IRI and FPCI variables, respectively.

Antecedent: Age of pavement since its construction
Linguistic terms (groups): [New Pavement (PN); Middle age Pavement (PM); Old Pavement (PA)]
Universe (ID): 0 to 20 years

ID	GROUPS														
	PN					PM					PA				
	0	0,25	0,5	0,75	1	0	0,25	0,5	0,75	1	0	0,25	0,5	0,75	1
0	○	○	○	○	●	●	○	○	○	○	●	○	○	○	○
2	○	○	○	●	○	○	●	○	○	○	●	○	○	○	○
4	○	○	●	○	○	○	○	●	○	○	●	○	○	○	○
6	○	●	○	○	○	○	○	○	●	○	●	○	○	○	○
8	●	○	○	○	○	○	○	○	○	●	●	○	○	○	○
10	●	○	○	○	○	○	○	○	●	○	○	●	○	○	○
12	●	○	○	○	○	○	○	●	○	○	○	○	●	○	○
14	●	○	○	○	○	○	●	○	○	○	○	○	○	●	○
16	●	○	○	○	○	●	○	○	○	○	○	○	○	○	●
18	●	○	○	○	○	●	○	○	○	○	○	○	○	○	●
20	●	○	○	○	○	●	○	○	○	○	○	○	○	○	●

Note: The degree of truth ranges from 0 to 1, in which 0 means that the numerical value definitely does not belong to the group and 1 means that it totally belongs.

The sum of Degrees of Truth on the same row must be equal to 1.

Figure 1. Example of form for age of pavement filled out for variable ID.
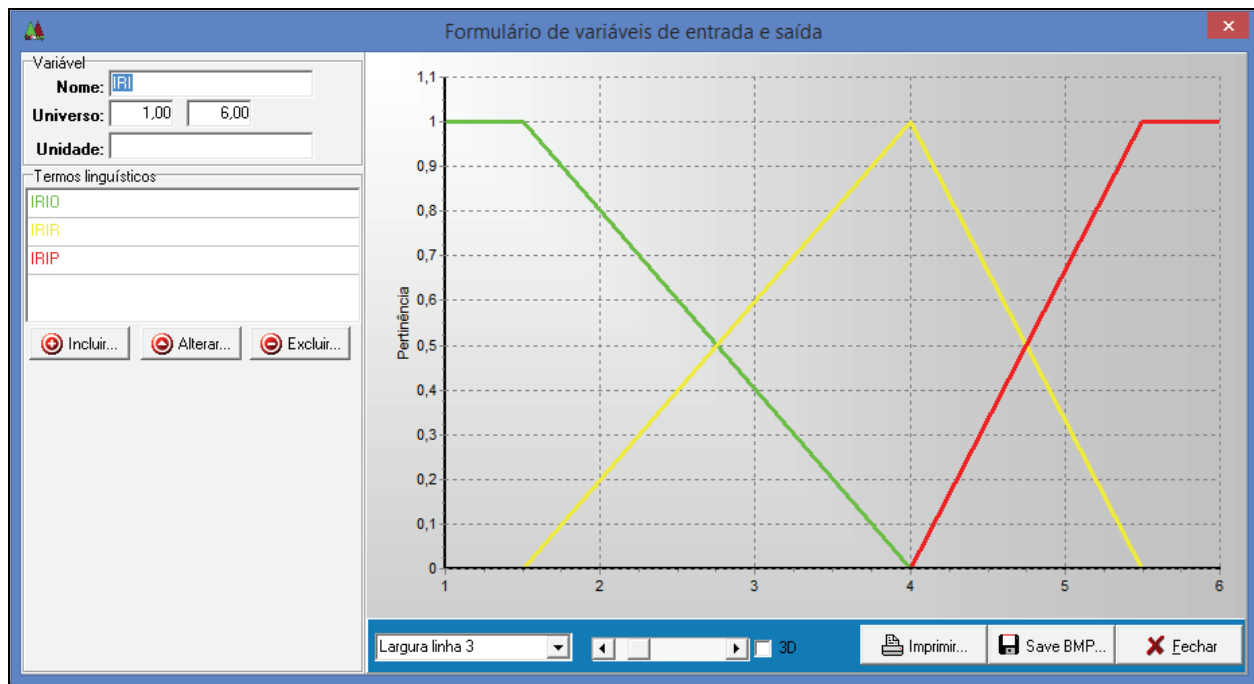
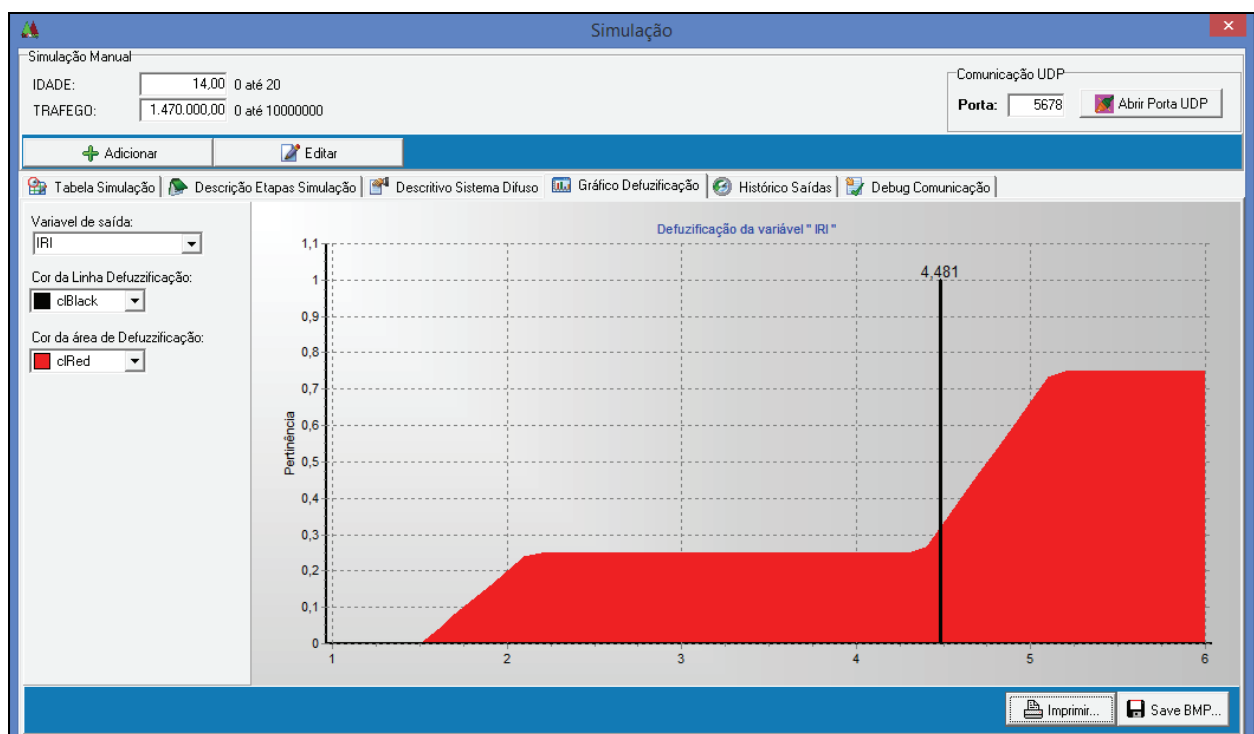**Figure 2.** Fuzzy modeling of IRI in the software InFuzzy.

**Figure 3.** Result of defuzzification of IRI in the software InFuzzy.

**Table 1.** Observed and calculated values of IRI from fuzzy model.

DERBA Code	Age	N	IRI (Observed)	IRI (Calculated)	Residues
420BBA0218-1	7	1,80E+05	2,64	2,79	-0,15
122BBA0500-2	17	2.70E+05	5.23	4.12	1.11
026EBA0085	18	2.80E+05	4.23	4.15	0.08
120EBA0255	15	1.70E+05	4.42	3.80	0.62
233EBA0025	19	2.00E+05	3.37	3.96	-0.59
148EBA0125	14	1.38E+06	4.86	4.48	0.38
148EBA0140	20	1.73E+06	5.01	5.30	-0.29
650EBA0020	11	1.39E+05	4.20	3.08	1.12
884EBA0005	14	5.11E+05	4.29	4.48	-0.19
262EBA0115	14	1.47E+06	4.88	4.48	0.40

Table 2. Observed and calculated values of FPCI from fuzzy model.

DERBA Code	Age	N	FPCI (Observed)	FPCI (Calculated)	Residues
420BBA0218-2	7	1.80E+05	4.0	3.25	0.75
084EBA0020	10	8.60E+05	2.0	2.29	-0.29
120EBA0255	15	1.70E+05	2.1	2.30	-0.20
233EBA0040	10	1.30E+05	3.0	3.15	-0.15
650EBA0020	6	8.40E+04	2.7	3.57	-0.87
349BBA0410-1	9	1.80E+05	4.0	3.12	0.88
349BBA0432	9	3.70E+05	3.5	2.62	0.88
420BBA0218-1	7	1.80E+05	4.0	3.25	0.75
489BBA0010	13	5.20E+05	2.7	1.78	0.92
120EBA0035	19	3.50E+05	2.6	1.64	0.96
120EBA0065	17	3.30E+05	1.3	1.72	-0.42
120EBA0250	15	1.70E+05	2.8	2.30	0.50
131EBA0110	10	5.10E+04	3.0	3.36	-0.36
142EBA0065	6	1.30E+05	3.5	3.40	0.10
142EBA0070	8	1.60E+05	3.5	3.32	0.18
152EBA0045	12	4.80E+05	1.5	2.02	-0.52

For measuring the goodness of fit of fuzzy models, a straight line fit was used to relate the predicted to the observed data. The corresponding correlation coefficient (r) (Figure 4 and 5) was also determined and the residual analysis (Figure 6 and 7) was performed. For IRI, a correlation coefficient equal to r = 0.71 was found, and for FPCI, a correlation coefficient equal to r = 0.70 was obtained.
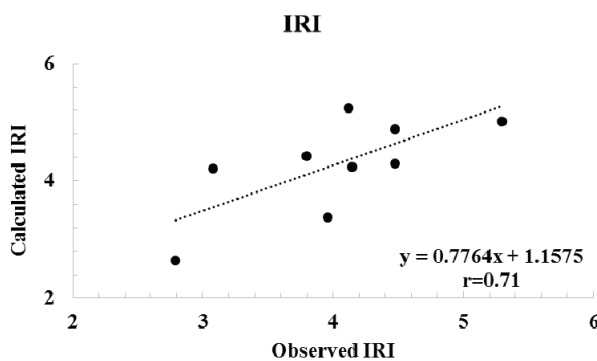
Figure 4. Correlation between observed IRI and with those predicted by the fuzzy model.
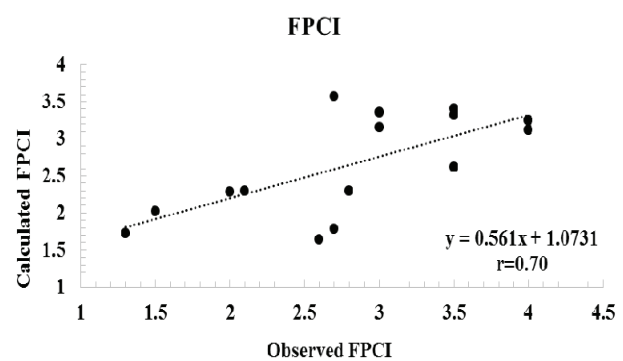
Figure 5. Correlation between observed FPCI values with those predicted by the fuzzy model.
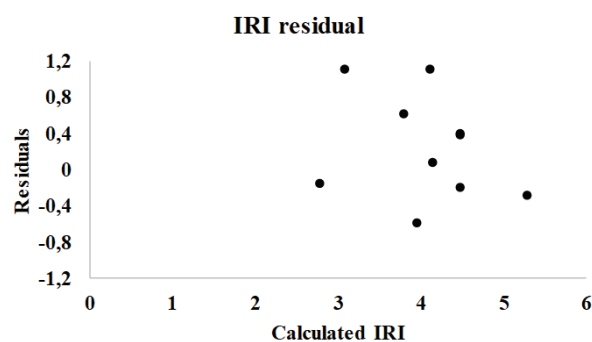
Figure 6. Residual graph of fuzzy model for IRI.
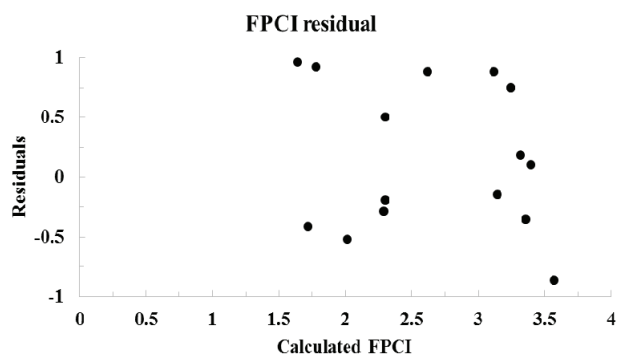
Figure 7. Residual graph of fuzzy model for FPCI.

Conclusion

In this research, pavement performance models were developed based on fuzzy logic to predict the International Roughness Index (IRI) and the Flexible Pavement Condition Index (FPCI). The goodness of fit was measured through a straight line adjustment and correlation coefficients of 0.71 and 0.70 were obtained for IRI and FCPI, respectively. This study showed that the fuzzy logic can be used to model variables related to flexible pavement deterioration, based on the knowledge of pavement management experts and can be used as an alternative tool, when there is no historical data of a given highway section.

Acknowledgements

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